NEURAL NETWORK DETECTION OF VENTRICULAR LATE POTENTIALS IN ECG SIGNALS USING WAVELET TRANSFORM EXTRACTED PARAMETERS

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Abstract- **After recovery from acute myocardial infarction (MI), a significant number of patients remain at risk of sudden death, which is attributed to ventricular tachycardia (VT). Ventricular Late Potentials (VLPs) are associated with VT. VLPs are low amplitude high frequency signals that appear at the end of the QRS complex of an ECG recording. In this work, discrete Wavelet Transform (DWT) and Artificial Neural Networks (ANN) are applied in the analysis of ECG signals in order to identify VLPs. Results of this analysis are used to classify patients with and without VLPs in their ECGs. DWT were computed for a total of (38) different ECG records that included control signals and signals for patients with VT. A set of parameters were extracted from WT and used as inputs to neural networks for the classification. Multilayer feedforward ANNs employing the back-propagation (BP) learning algorithm were trained and tested using the WT extracted parameters.**
***Keywords*: Ventricular Late Potential (VLP); Discrete Wavelet Transform (DWT); Artificial Neural Networks (ANN); Electrocardiography (ECG).**

I. INTRODUCTION

Analyzing electrocardiographic (ECG) signals includes not only inspection of P, T and QRS waves, but also important hidden information such as Ventricular Late Potentials (VLP), that might be extracted from high-resolution recordings through advanced signal processing. These VLPs are low-amplitude high-frequency potentials that have been observed in ECG signals of patients after myocardial infarction (MI) and considered as a noninvasive indicator of Ventricular Tachycardia (VT). Previous studies have shown that patients without VLP in their ECGs have a greater chance of survival than those having VLP. The task of identifying VLP is by no means an easy one to achieve due to the composite nature of ECG signals, (i.e. combination of signal and noise). In addition, the low amplitude of the desired signal (VLP), which is in the order of 40 μv, embedded in high amplitude QRS complex in the order of one milli-volt and the nonstationarity of the ECG signals. ANNs can be used to facilitate the automatic identification of MI patients with and without VLP.

II.METHODOLOGY

The methodology employed in this work consists of the following stages, 1) taking the wavelet transform of the three X,Y and Z leads , 2) parameter extraction, 3) design, train and test neural networks. In the WT transform stage of the process, the chosen levels of the WT of the three leads were combined to form the filtered QRS complex. The area under this filtered

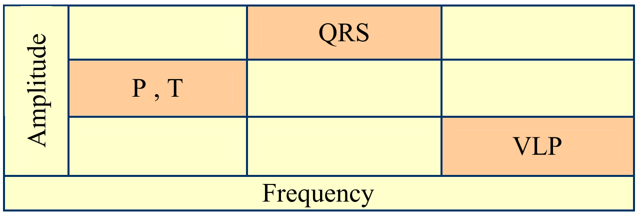

Fig. 1 Frequency distribution of different ECG components.

QRS was calculated for each signal and used as one of the parameters. The second parameter was the norm of level-6 and level-7 combined together. These parameters were used as an input set to the ANN for classification purposes.

A. ECG signals and Ventricular Late Potentials

The frequency distributions of ECG signals are classified as lower frequency P and T waves, middle-to-high frequency QRS complex and high frequency late potentials when they exist [1]. The P and T waves are medium-amplitude low-frequency signals (MALFS), the QRS complex is high-amplitude medium-frequency signal (HAMFS) and the VLP is a low-amplitude high-frequency signal (LAHFS). Fig. 1 shows a diagram of the different frequency components presented against their respective strengths.

Characteristic changes in these waves are an indication of possible abnormalities. Late in the ECG cycle, when high frequency events occur, these low-amplitude signals are identified as late potentials. Late potentials or VLP have been shown to be a predictive of arrhythmia of the heart.

When arrhythmias, such as tachycardia do occur, the QRS undergoes important morphological changes. These changes may be in form of a widening of the QRS. As the QRS widens, its power spectra shows diminished contributions at higher frequencies and these are spread out over a wider body of signal. This empirical description of time-domain features of the ECG signal lends itself particularly well to analysis by time-frequency and time-scale methods.

In previous studies a low-amplitude, high frequency signal in the last 40 ms of the filtered QRS and a prolonged QRS duration have been shown to identify patients with ventricular tachycardia A late potential was defined as a low-amplitude signal 20 μv in the last 40 ms of the filtered QRS complex and a long filtered QRS complex was defined

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Abstract

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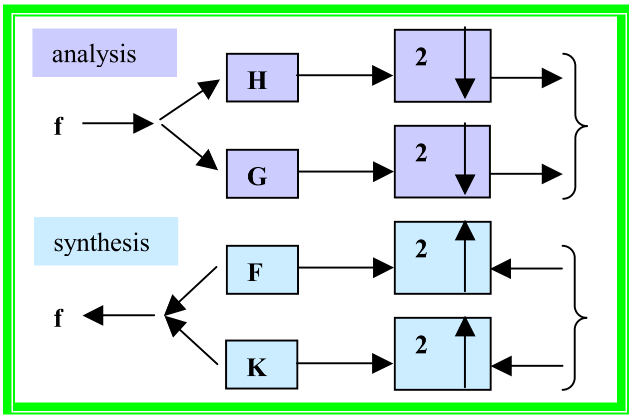

Fig. 2 Forward and inverse WT

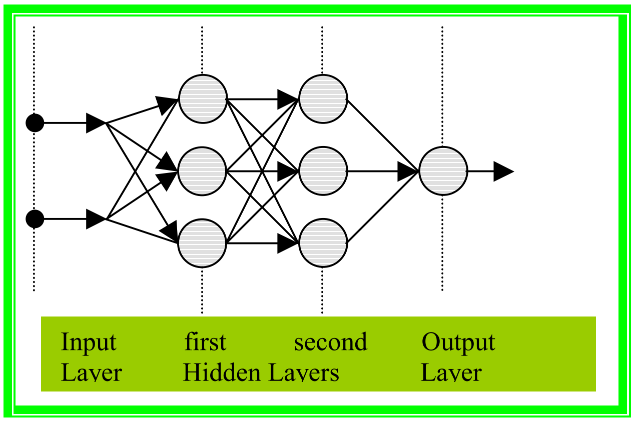

Fig. 3 Multilayer feedforward ANN

as total filtered QRS duration greater than 120 ms where filtering in our case was carried out using the wavelet transform. The presence of late potential and/or long QRS is defined as a marker of abnormality such as ventricular tachycardia. [2][3][4][5].

B. Wavelet transform: a time-scale distribution

The wavelet transform is a special case of perfect reconstruction filter banks. The main idea of the transform is to subdivide arbitrary signals into constant frequency bands using recursive filter banks generated from a small number of prototype filters.

The filtering process is equivalent to decomposing the signal using a set of basis functions that are localized in both space and frequency and which are scaled and shifted versions of a prototype mother wavelet.

In discrete time, scale changes are discrete. Scaling for this case involves sampling rate changes and resolution is directly related to scale. The WT of a continuous signal is defined as:

$$WT\,(x(t), b, a) = \sqrt{a}\int_{-\infty}^{\infty} x(at)h^{*}(t - b/a)dt \qquad (1)$$

Analysis of x(t) is carried out by the use of a special function h(t), called mother wavelet. This function is translated in time for selecting that part of the signal to be analyzed. The selected portion of the signal is then expanded or contracted using a scale parameter a, which is analogous to frequency [5]. For small values of a, the wavelet is a narrow version of the original function, which corresponds roughly to high frequency.

For large values of a, the wavelet is expanded and corresponds to low frequencies. WT can be realized using a pair of FIR filters H and G, which are low-pass and high-pass respectively, Together, these filters define analysis-synthesis scheme as shown in Fig (2). Where F is the adjoint of H and K is the adjoint of G and are related according to (2).

$$\begin{aligned} &F(Z) = G(-Z)\\ &K(Z) = -H(-Z)\\ &H(Z)G(-Z) - G(Z)H(-Z) = 2 \end{aligned} \qquad (2)$$

These relationships are chosen in order to eliminate aliasing, phase and amplitude distortion in the reconstructed signal. This convolution-decimation process has several important properties, 1). In exact mathematical terms it allows for perfect reconstruction of the original signal. 2) It can be applied recursively. 3) The forward/inverse WT are elegant in their simplicity, requiring only convolution and up/down sampling, [12].

C. Neural Networks

A neural network has a parallel-distributed architecture that contains a large number of simple neuron like processing elements and a large number of weighted connections between the elements. The weights on the connections encode the knowledge of a network. The intelligence of a neural network emerges from the collective behavior of neurons, each of which performs only very limited operation.

The topology of a neural network refers to its framework as well as its interconnection scheme. The number of input layers, hidden layers, output layers and the number of nodes per layer often specify the framework. A multi-layer perceptron (MLP), which is, a feed-forward network is chosen as a neural network structure for this study.

Each artificial neuron receives a set of inputs, which are multiplied by a weight analogous to synaptic strength. The sum of all weighted inputs determines the degree of firing called the activation level. Each input X[n] is modulated by a weight W{n} and the total input is expressed as:

$$v_j(n) = \sum_n X[n\}W[n] \qquad (3)$$

or in vector form **X.W** where:
X = [x1, x2, … ,xn] and **W** = [w1, w2, …, wn].

The input signal is further processed by the *activation function* to produce the output signal, which if not zero, is transmitted along. The ability of learning through training set is significant in the study to improve the classification performance of the network, [13][14][15].

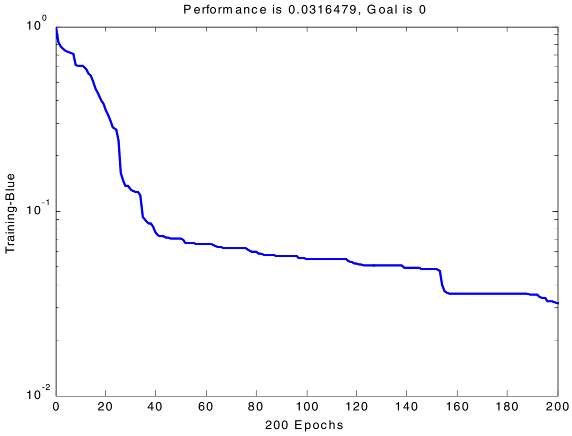

Fig. (4) A sample of the training performance.

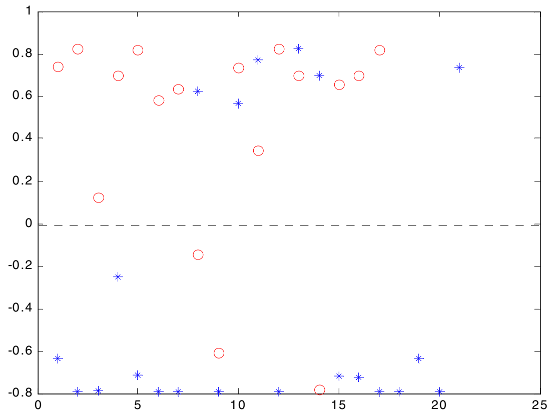

Fig. (5) Classification using only classical parameters. normal (o) and abnormal signals (*).

Multi-layer perceptron (MLP), which is a feed-forward network, is chosen as a neural network structure for this work. A network containing two hidden layers with three neurons for each layer was designed and trained using the back-propagation learning algorithm as shown in Fig. 3. The network was trained for a number of times and the best result for the data set was chosen. The data set recorded and classified by experts at the Sussex University, England. The set included a total of (38) with (17) normal ECG signals and (21) signals with VT. Five signals from each category were used as training set for the network with the remaining signals used for testing. The network was simulated with 50,100,150 and 200 epochs. . A sample of the training performance for the network is shown in Fig. 4. The first layer had its weights coming from the three inputs and the last layer consisted of a single neuron and represented the output. The hyperbolic tangent function was used as the nonlinear activation function. This commonly used form of sigmoid nonlinear function in its most general form is defined as:

$$\varphi[v_j(n)] = a\tanh(b v_j(n)) \quad ,(a,b) > 0 \qquad (4)$$

where *a* and *b* are constants.

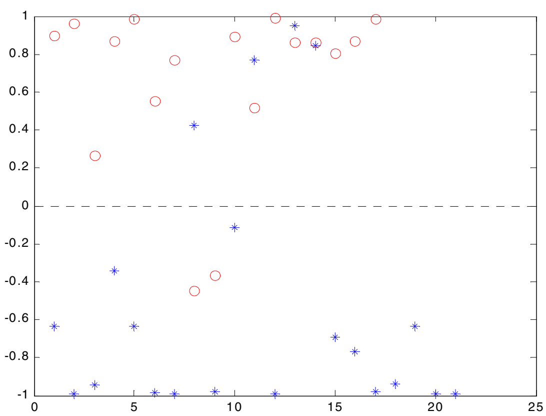

Fig. (5) Classification using only WT parameters. normal (o) and abnormal signals (*).

III. RESULTS AND CONCLUSION

First the signals were visually compared using the two WT extracted parameters. The two parameters were adequate to classify the signals completely with a set of threshold. The first Parameter represents the power in vector magnitude and the second parameter represents the cross-term component resulting from the multiplication of level-6 with level-7. With only the two WT extracted parameters used, as input to ANN did not produce the same classification results as the visual comparison in the previous step. The result of this part is presented in Fig. (5). The next step was the application of the three classical parameters, i.e., QRS duration, voltage in the terminal of the QRS and the duration of the low amplitude terminal signal. The result of this part is presented in Fig. (6) and as can be seen did not give acceptable classification results. The results of these two steps are close with a little advantage with the use of WT extracted parameters. Finally all five parameters were applied as input to the neural network. The results of this part gave a 100% classification of all signals in our data set without exception with dividing region from –0.2 to +0.2 level as indicated in Fig. (7). The symbol (o) represents signals for normal subjects while; symbol (*) represents those with VLP in their ECG recordings.

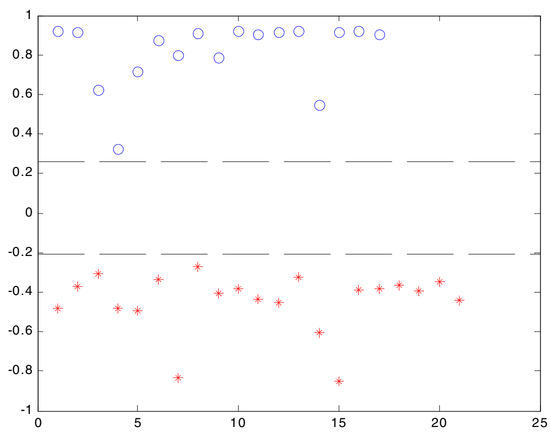

Fig (7) Classification using both WT and classical parameters normal (o) and abnormal signals (*).

Table 1 Classification results.

	WTP		*CP*		*WTP + CP*	
	S	F	S	F	S	F
Normal	15	2	14	3	17	0
VT	17	4	15	6	21	0
Total	32	6	29	9	38	0
%	84.21	15.79	76.32	23.68	100	0.0

In this work we attempted to improve the ability to classify signals originated from different categories of patients. Table 1 summarizes the result obtained and lists number of signals in each category. The results are classified as Fail (F), Success (S) with all three procedures; the WT parameters (WTP), the classical parameters (CP) and using all parameters from both categories. The success percentage was 84.21% for WTP and was 76.32% for CP while it was 100% for the two groups of parameters together. The main distinction between the two categories presented is the absence or presence of what is known as VLP. By introducing new parameters to be used in the classification we were able to get better results at the cost of increasing the calculation and analysis part. The joint use of the WT with artificial neural networks gives an extended capability into the analysis and study of signals in general and in particular to signals of biological origin. This approach will be investigated in our future work.

The result obtained in this study are encouraging and will be the basis for further investigation with future aim of acquiring more data for further validation. Currently the authors are designing a high-resolution data acquisition system that will be used for this purpose.

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